Gear Pitting Fault Diagnosis Using Domain Generalizations and Specialization Techniques

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ABSTRACT

Gear pitting is a common gear fault, which has been an important subject to industry and research community, In the past, the diagnosis of gear pitting faults was all based on fixed operating conditions and the fixed gear health state, which is a in-set detection, However, in real industrial scenarios, gear pitting fault diagnosis is always an open-set detection, in which the working conditions and the gear health state are commonly not known in advance. In order to deal with this open-set detection problem, we proposed a three-stage diagnosis method. In the first stage, we built an in-set health state classification model based on Domain2Vec to solve the domain generalization problem caused by different operating conditions. In the second stage, we modify the classification model to a regression model to predict the out-of-set health state sample in the dataset. In the third stage, we used KNN algorithm to correct the wrong model in the second stage and further improve the accuracy of classification. Our proposed method achieved scores of 463.5 and 472 on the test set and validation set, respectively, and ranked first in the 2023 PHM Conference Data Chanllenge.

1. METHODS

Before the detection, to enhance the network's performance prior to training, preprocessing the signals and extracting shared features from them can yield improved outcomes, we employ a sequential process involving normalization, segmentation, sampling, and short-time Fourier transform (STFT) on the signal. The specific process is shown in Figure 1. Then we split this task into two parts, ”in-set” health states (iHS) detection and ”out-of-set” health states (oHS), which is divided according to whether the pitting degradation level can be observed in advance. we employed a three-stage model for predicting the health states (HS) of gears, which can be summarized as Classification Model of iHS, Regression Model of oHS and Modification of KNN.

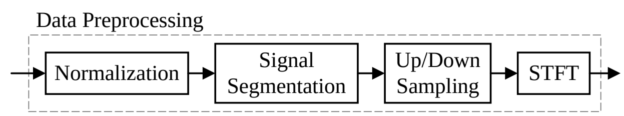

Figure 1. Process of data preprocessing. The original data should undergo a series of sequential operations, including normalization, signal segmentation, sampling, and STFT.

1.1. Classification Model of iHS

In the first stage of the model, we employed the Domain2Vec to specifically target the prediction of iHS samples (pitting degradation levels 0, 1, 2, 3, 4, 6 and 8). The Domain2Vec structure used in this article is shown in Figure 2. We utilizes EfficientNet-B0 as the feature extraction network. To classify pitting degradation levels across diverse operating conditions (speed/torque) and enhance the model's robustness, we try to disentangle the initial features into specific features corresponding to operating conditions and HS and incorporate the adversarial training to achieve a more comprehensive feature disentanglement. Additionally, we introduce a reconstruction module to prevent information loss, as shown in the right part of Figure 2.

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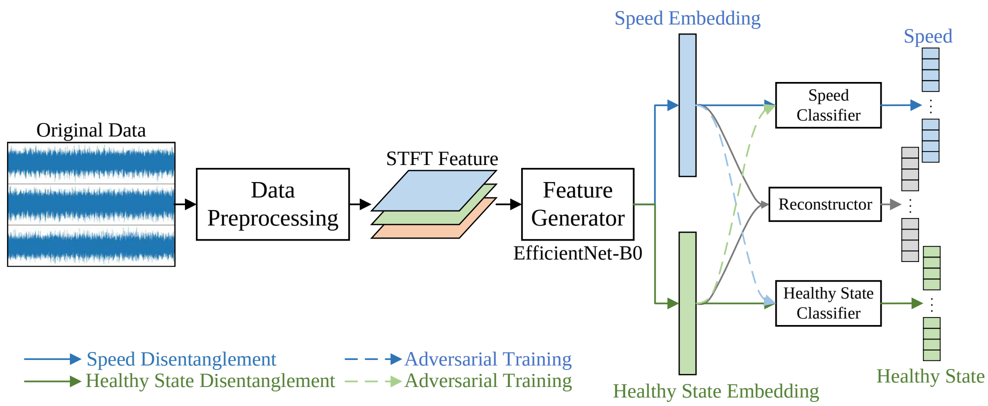

Figure 2. Domain2Vec structure diagram for first stage .

1.2. Regression Model of oHS

In the second stage, we developed a regression model to predict oHS (pitting degradation levels 5, 7, 9, 10). The regression model is derived by modifying the final layer of the classifier to include a linear layer dedicated to regression, while building upon the foundation of the one-stage classification model. In order to better fit the mapping relationship between input features and pitting degradation level, we replace the activation function of the last layer with an improved sigmoid function. The formula for the improved sigmoid function is shown in Eq. 1, the diagram is shown in Figure 3

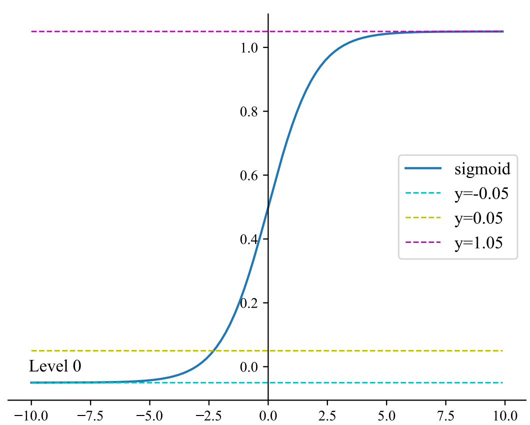

Figure 3. Image of the improved sigmoid function. The pink dashed line and cyan dashed line represent the upper and lower bounds of the function, respectively. The region between the cyan dashed line and the yellow dashed line corresponds to the pitting degradation level 0.

$$sigmoid_{large}(x) = \frac{1.1}{1+e^{-x}} - 0.05 \tag{1}$$

1.3. KNN of iHS

Compared to the known-class classification model, the regression model provides a greater range of output possibilities. To maximize the inclusion of oHS samples from the dataset, we opt for a model with fewer iterations (typically within 10 epochs). But this model selection will led to the misclassification of some iHS samples into the oHS categories. By comparing the distance between the test set sample and the training set samples and selecting the k samples with the smallest distances, we can then assess whether the prediction results for the samples need to be updated by comparing the average distance to the predefined threshold.

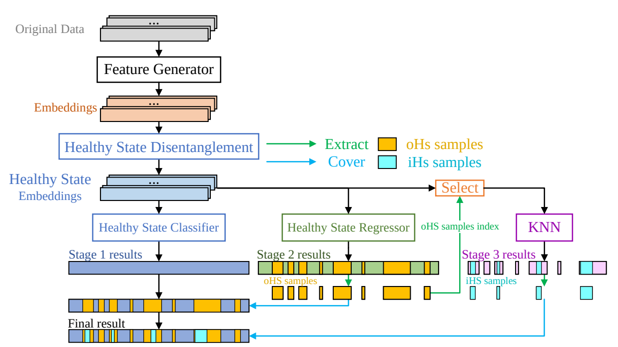

Figure 4. Sub-sample voting diagram.

1.4. Result fusion

After obtaining the results of the three stages, we need to extract, process and cover the results of the three models in turn. The resulting fusion diagram is shown in the Figure 4.

The results of the first stage classification model are built as the basis. Samples predicted to be oHS were extracted from the results of the regression model of the second stage and covered in the results of the first stage. According to the index of oHS samples detected in the second stage, the corresponding healthy state embeddings were selected and input into the KNN model. The samples predicted as iHS are selected from the prediction results of KNN and covered in the basic results to get the final prediction results.